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This paper describes a representation and a set of inference methods that combine logic programming techniques with probabilistic network representations for uncertainty (influence diagrams). The techniques emphasize the dynamic construction and solution of probabilistic and decision-theoretic models for complex and uncertain domains. Geven a query, a logical proof is produced if possible; if not, an influence diagram based on the query and the knowledge of the decision domain is produced and subsequently solved. A uniform declarative, first-order knowledge representation is combined with a set of integrated inference procedures for logical, probabilistic, and decision-theoretic reasoning.

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Decision Tree Induction Systems: A Bayesian Analysis

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Decision tree induction systems are being used for knowledge acquisition. Yet they have been developed without proper regard for the subjective Bayesian theory of inductive inference. This paper examines the problem tackled by these systems from the Bayesian view in order to interpret the systems and the heuristic methods they use. It is shown that decision tree systems depart from the usual Bayesian methods by implicitly incorporating prior belief that the simpler of two hypotheses will be preferred, all else being equal. They perform a greedy search of the space of rules to find one in which there is strong posterior belief.

The Automatic Training of Rule Bases that Use Numerical Uncertainty Representations

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The use of numerical uncertainty representations allows better modeling of some aspects of human evidential reasoning. It also makes knowledge acquisition and system development, test, and modification more difficult.

It is proposed that where possible the assignment and/or refinement of rule weights should be performed automatically. The authors present one approach to performing this

training—numerical optimization—and report on the results of some preliminary tests in training rule bases. They also show that truth maintenance can be used to make the training more efficient and ask some epistemological questions raised by training rule weights.

A Study of Associative Evidential Reasoning

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Evidential reasoning is cast as the problem of simplifying the evidence-hypothesis relation and constructing combination formulas that possess certain testable properties. Important classes of evidence as identifiers, annihilators, and idempotents and their roles in determining binary operations on intervals of reals are discussed. The appropriate way of constructing formulas for combining evidence and their limitations—for instance, in robustness—are presented.

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Stochastic Simulation of Bayesian Belief Networks

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This paper examines the use of stochastic simulation of Bayesian belief networks as a method for computing the probabilities of values of variables. Specifically, it examines the use of a scheme described by Henrion, called logic sampling, and an extension to that scheme described by Pearl. The scheme devised by Pearl allows us to "clamp" any number of variables to given values and to conduct stochastic simulation on the resulting network. This algorithm, in certain networks, leads to much slower than expected convergence to the true posterior probability. This behavior is a result of the tendency for local areas in the graph to become fixed through many stochastic iterations. The length of this nonconvergence can be made arbitrarily long by strengthening the dependency between two nodes. This paper describes the use of graph modification. By modifying a belief network through the use of pruning, arc reversal, and node reduction, it may be possible to convert the network to a form that is computationally more efficient for stochastic simulation.

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